“Allocation of Ridesharing Facilities Using a Shareability Assessment Model”

Case Study: Ann Arbor, Michigan

by

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Dedicated to:

My Love, Babak

And

My Parents, Afrooz and Hedayat

Who always picked me up on time and

encouraged me to go on every adventure,

especially this one.

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Abstract

With the increased environmental awareness during recent years, more people are aware of the social and environmental burdens of car transits. Meanwhile, emerging trends in science and society have increased the demand for improving mobility-as-a-service (MAAS). These services can reduce Green House Gas (GHG) emissions, decrease time and cost of travel, improve equity, enhance safety, reduce congestion, and ensure sustainable economic growth. To achieve such benefits, more investments are needed on the shared mobility systems. Ridesharing is a type of mobility services that let two or more people to share a ride which is operated by a third party.

By using the geographically coordinated vehicle trips' data, this thesis develops a framework to find shareable trips and then, to allocate ridesharing stations. The results identify potential hot areas for forming ridesharing trips, optimum locations for ridesharing facilities (considering the available facilities assets in the proposed areas) and finally, a rough estimate of the potential impacts of the proposed system. Overall, findings of this research provide implications for policy makers, urban planners and ridesharing corporates to develop strategies to encourage ridesharing and to improve the quality of these services.

This research shows that by locating six stations with a maximum wait time of 7.5 minutes for ridesharing in the city of Ann Arbor in the proposed areas, 97% of all urban trips can be shared. This system has a potential to save 2246 mile of

Vehicle Mile Traveled (VMT) every day which can lead to cutting 39 gr of CH_4, 8 gr of N_2O, and 923106 gr of CO_2 from the current daily level of emissions.

Introduction

Since the invention of cars, demand for car ownership is rapidly growing all over the world, especially in developed countries. This rapid growth has led to an increase in the allocation of resources in transportation systems, especially roads and parking lots in order to properly respond to the increased demand for these facilities. While cars were meant to provide safer and faster mobility options for citizens, conversely has resulted in traffic congestion and environmental pollution. Current trends in personal vehicles ridership have increased direct costs of car trips, like the cost of fuel and maintenance. The commute of privately-owned vehicles is not just costly for drivers, but in fact, each trip can impose enormous marginal costs to society. To mention a few, according to the inventory of 1990–2015 US GHG Emissions and Sinks published by EPA, after electricity generation sector, transportation is the second major source of greenhouse gas emissions in the United States. Meanwhile, road transportation is responsible for the largest share of transportation CO2 emissions as well as fuel use, compared to aviation, rail, and marine transportation. Personal transportation by car (light-duty vehicles including passenger cars and light-duty trucks) is the largest emitter with the share of 61% of transportation emissions in the U.S. [20]

There are also several reports from health agencies that highlight the health concerns associated with urban mobility. As a primary report from the National Safety Council indicates, 38,300 people died in motor-vehicle accidents at 2015. [14] Not only car accidents, but also automobiles exhaust has been proven to threat human health. Mostly but not limited to winter, lots of the major cities around the world, especially in developing countries are experiencing extremely polluted days when the level of pollutants in the air fell in the hazardous zone for citizens.

In a broader context, privately owned vehicles are also burdensome for cities. No need to mention that the high annual cost of road building and maintenance projects, as well as preparing parking spaces, especially in downtown areas. But it is not the whole problem; people often forget to count the cost of the lost opportunities for inner-city developments in favor of building new roads and parking spaces.

Urban car trips also have increased out-of-pocket costs, like the lost opportunity costs and mental discomforts. However, the cost of purchasing an automobile and its annual insurance are still the main cost of car ownership. According to the reports, these privately-owned, individually-driven, gas-powered vehicles sit unused 95% of the time, and cost over $1 trillion annually. [17]

As these problems have gotten much worse, transportation planners started working on new modes of transportation that have fewer marginal and social costs for everyone. With new improvements in information technology, ridesharing has emerged to increase accessibility in a sustainable manner and decrease direct cost and the marginal cost of urban trips for people.

Ride-sharing as a solution

Emerging trends in science and society are pushing forward the whole transportation planning process to create opportunities for new mobility options that can reduce GHG emissions, decrease time and cost of travel, improve equity, enhance safety, reduce congestion, and ensure sustainable economic growth. On the future transportation horizon, mobility is a service, available when and where it is needed -just in time- allowing fewer vehicles to do the same job at lower cost.

To achieve such benefits, more investments greater investments are required in the field of shared mobility. The growing ubiquity of mobile Internet technology has created an opportunity to bring together people with similar itineraries and time schedules to share rides on a short-notice. ([1], P:1450) Also, by taking advantage of improvements in Information Technology (IT) and clean vehicle industry, ridesharing can have further significant environmental benefits.

The general idea of ridesharing is to share non-private vehicles between several users making trips. ([3], P:238) In fact, sharing a ride is a way to utilize the empty seats in a ridesharing vehicle. Ridesharing is an alternative travel mode that is more flexible than public transit and less expensive than private car ownership. ([8], P: 267)

Ridesharing has potentials for reducing fuel consumption, traffic congestion and transport cost. ([14], P: 12) Also by reducing the number of operating vehicles from users of this service, ridesharing also can reduce parking requirement.

Benefits associated with ride-sharing can be categorized into three groups:

1. **Environmental**
   - Less energy usage
   - Fewer emissions and pollutants
   - Preserved natural landscape from future urban growth
   - Enhanced sustainability
2. **Financial**
   - Fewer the need for personal car
   - Saved budget for customers and municipalities by cutting the need for new parking facilities
3. **Sustainable Urban Development**
   - Greater safety
   - Less congestion

- Better land use
- Enhanced Mobility
- Less need for road expansion

These benefits can be achieved if ride-sharing becomes more reliable and accessible. Automation can increase the reliability of ride-sharing by decreasing the effort and amount of time that a driver or participant spend to find a match while also reducing the cost per trip for every participant. ([1], P: 1450) Previous researches have shown that the location of stations where shared-rides begin or end is also critical to make ride-sharing services accessible. In other words, allocation of the ridesharing facilities in high-density areas with good walking, cycling and transit options will increase the efficiency of the system as well as the number of people who use it. The more accessible the stations, the greater the demand for ride-sharing.

Thus, if we want to have a more cherished environment and sustainable urban development, we need to put effort into developing systems that optimize and facilitate ridesharing services. This can be done by developing more accurate algorithms for finding ride matches and integrating the allocation of ride-sharing facilities with other land use and transportation plans.

Research questions

The current literature around ridesharing mainly focuses on developing optimized models for finding ride matches in dynamic ridesharing systems. However, limited attention is paid to studying the static ridesharing models and planning to manage future demand for these services at the city level. As static ridesharing models arrange trips that are known in advance ([13]: 64), incorporating ridesharing in these models into transportation planning decisions can improve accessibility within the cities and reduce dependency on privately owned vehicles. This research is aimed at filling this gap by developing a static ridesharing model based on the spatial position and time differences between locations. This model can predict future demand for ridesharing in urban areas and allocate necessary facilities to meet the future needs. Using Ann Arbor, MI as the research case study, this thesis aims to answer the following questions:

- How can shareable trips be identified?
- How should public ridesharing stations be sited to maximize shareability and potential environmental benefits?
- How much air pollutants and emissions can be reduced from implementing ridesharing systems in city of Ann Arbor?

There is not that much work done on clarifying the importance of ridesharing facilities. However, as a dynamic system, optimum locations of these stations can considerably improve the functionality and sustainability of the system. Especially in low-density areas where door-to-door service may not be economically feasible or in high-density areas where alighting can disrupt traffic flows and/or endanger the passengers and pedestrians. ([17], P: 2)

These stations can be multi-functional for ridesharing purposes. For example, they can be used as parking spaces when the ridesharing vehicle is idle (and is waiting for a call or), where reserved vehicles can remain reserved until rush hour to guarantee the reliability of the system. These stations also can support the integrity of the system when electric vehicles are used as ridesharing vehicles. This means that electric vehicles within the system can use ridesharing facilities to quickly recharge and return back to the system in a short time.

Methods

The analytical framework of this thesis has two major components: Shareability Assessment and Geographic Allocation of Ridesharing Facilities (Figure 1) The Shareability Assessment part uses coordinates of origins and destinations as the model inputs and then will identify nodes with high potentials for ridesharing. Ridesharing opportunities are assessed with respect to both the geographic location of trip origins and destinations as well as the time of the trip. Generally, the more nodes of trips, the more people will choose ridesharing services.

This can be accomplished using data from an instrumented vehicle equipped with Global Positioning Systems (GPS) technology. The second section of the framework, uses the Spatial Analyst toolset in ArcGIS 10.4.1 and identifies nodes from the previous step as model input. At this stage, a layer of nodes with high potentials for ride-sharing will be overlaid with currently available parking facilities. The output of the model will show the best locations for implementing ridesharing facilities. Finally, the environmental benefits of the proposed system will be calculated based on the number of shareable trips and consequently the amount of VMT saved.

Data

Data for this study was collected through a U.S Department Of Transportation (DOT) sponsored project in contribution with the University of Michigan Transportation Research Institute (UMTRI), called the Safety Pilot Program. This program is a research initiative that features real-world implementation of connected vehicle safety technologies, applications, and systems using everyday drivers. ([3], P:9) The purpose of the project was to understand travel patterns and ways to improve the safety of driving. Data includes trajectory data for more than 1,000,000 trips in Ann Arbor, Michigan from July 2012 to March 2013. Each data point includes a vehicle GPS device ID, a timestamp when a data point is recorded, the GPS location of the vehicles at the time of recording, GPS speed, average speed and the length of trip.

Model framework for allocation of ridesharing facilities

In order to identify the optimum locations for ridesharing facilities, this research consists of a couple of steps that can be categorized into two main categories. The first group includes a set of steps toward identifying shareable trips. This group is named the Shareability Assessment section. The Second section or the Geographic Allocation of Ridesharing Facilities uses the output of the previous part of the model and incorporates it into the existing condition of the city to optimally allocate ridesharing facilities. A schema of the model is shown in figure 1.

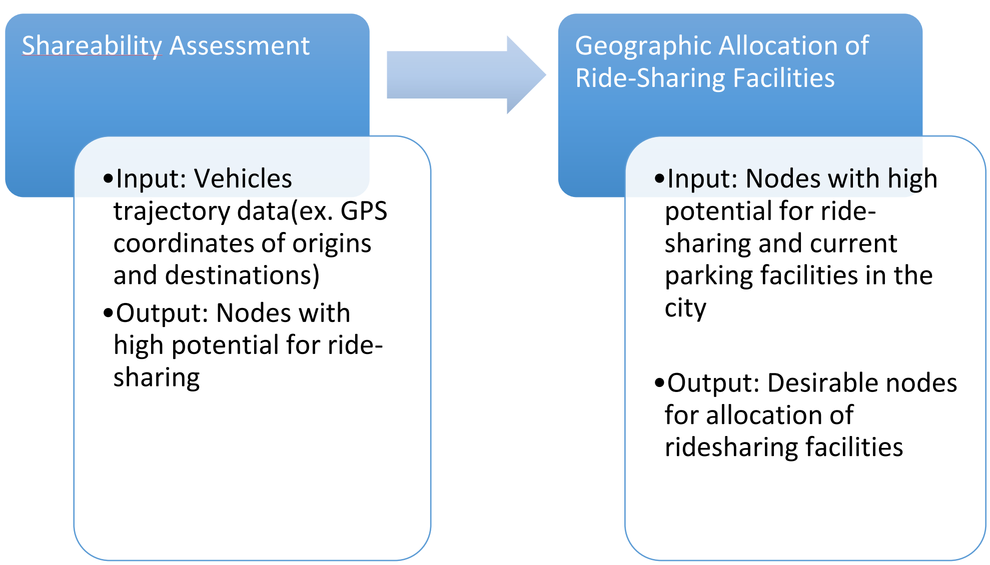

Figure 1: Model framework for allocation of ridesharing facilities

Part One: Shareability Assessment

As mentioned before, ridesharing is a function of many different variables. Aside from vehicle assignment concerns, the goal of this research is to find the most favorable locations for ridesharing in cities. In this regard, the following steps can explain the model.

First: Selecting a random 24 hours

As the very beginning step of the analysis, the functional unit of this thesis is defined as one day (24 hours). As our goal in this research is to identify the area that people frequently make their trips from/to, so we need to find patterns, not occasional occurrences. So, studying the desired area on a daily basis is helpful enough for this model. Hence, a random 24 hours will be selected for further analysis.

Second: Selecting the study area

Generally, the nature of urban trips in American cities is highly integrated with everyday commuting between home locations in the suburbs to the work locations in the cities or vice versa. In order to capture those trips and potentials for ridesharing, study area can be within a few miles from city limits. This distance may differ from one city to another. For this thesis's case study, a 2-mile distance is chosen based on the spatial distribution pattern of the trips.

Third: Identifying the most favorable trips' origins

Considering marginal benefits and personal concerns (ex: safety and comfort), it is also assumed that only two people will share a ride. [13: 13293] Based on the GPS locations where trips were started, we can identify which areas in the city have produced a high number of trips in every 24 hours. A heat map can clearly represent how intense the travel demand is in one area relative to other areas. This step and the following one are important to understand the initial pattern of travel distribution within the city and make a decision about the number of required number of clusters based on this.

Fourth: Identifying most favorable trips' destinations

Like the previous step, in order to identify the most favorable trips destinations we need to use GPS locations where trips end. On this stage, a heat map will be helpful to identify areas within the city with high trip absorption rates.

Fifth: Defining and identifying shareable trips

The ability to identify shareable trips depends mainly on two principles:

Wait time:

One of the most important factors of ridesharing is passengers' wait time. It is clear that the formation of ridesharing needs a passenger to devote some extra time to their regular trip to find a match.

Usually, the amount of deviation of trip departure and arrival time which is tolerable to the passengers is called “wait time”. Based on the fleet size and desired services, recent studies have considered a wide range of time for formation of ridesharing; from less than 1 minute to 10 and 15 minutes. ([2], [3], [6]-[9], [15]-[17], [23] & [24]) This period includes the time for loading/unloading passengers and also the time required for the vehicle to stop and start again, as well as time needed for passengers to get into and out of the car. It also takes into account the time that is needed for the vehicle to arrive at the first passenger’s place (passenger A).

As it was mentioned before, wait time is highly dependent on many other factors that may differ from case to case. So, in order to gain a more accurate estimation, it is highly recommended to design scenarios with different wait times. This can help finding the optimum wait time based on research case study attributes. For this research, three different scenarios for wait time, including 5, 7.5 and 10 minutes intervals, are considered as wait time options. The results are shown in the case study section.

Speed:

To calculate the distance between two potential points for ridesharing, in addition to the wait time, we also need to specify the average speed of vehicles. This could be done by finding the average speed in the study area or using recommended speed for the area. After finding the best speed and wait time, it is time to calculate a preferable distance between two nodes that have the potential for ridesharing. With a preferred wait time and speed, two nodes can share a trip if they meet the following condition:

i) Driving distance (A- B) <= speed (mile/ hour) * wait time (hour)

ii) Start time of trip B - start time of trip A <= wait time (minute)

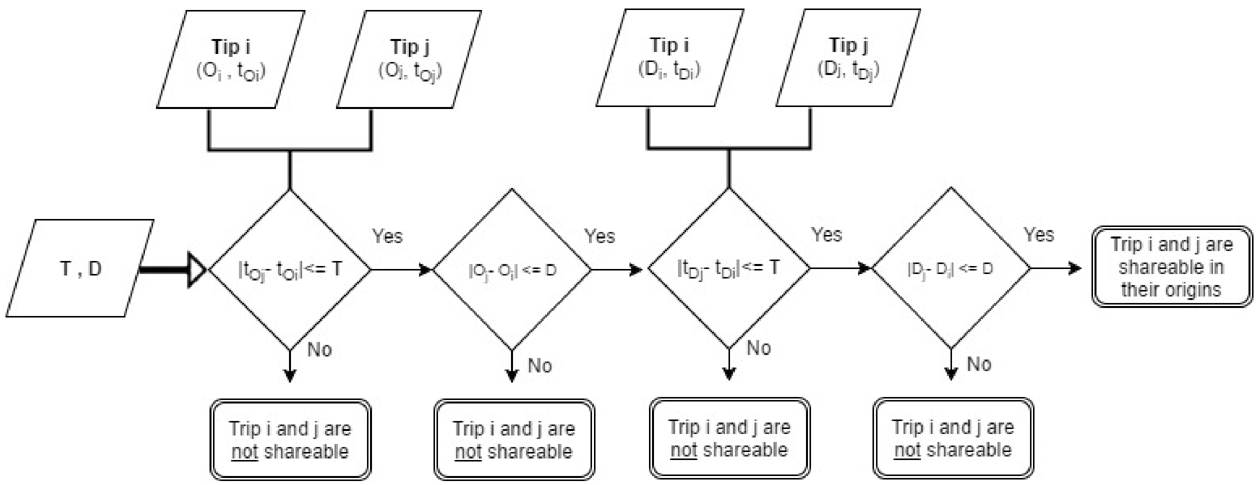

Figure 2: Ride matching algorithm

Where:

O_i, D_i, t_{Oi} & t_{Di} respectively represent the Location of the trip i origin, trip i destination, start time of trip i and finally end time of trip i.

T represents wait time and D stands for the desired distance between two trip nodes.

As it can be inferred from the graph, any node in the gray area has the potential to share a ride with point A. Then, based on latitude and longitude coordinates, the Haversine distance formula was used to calculate distance between two starting or ending points.

The following formula is used to calculate the distance between two coordinates:

HD (A, B) = R * arccos (sin(latA) * sin(latB) + cos(latA) * cos(latB) * cos(lonA-lonB))

However, it is obvious that the travel distance of a trip in a real-world situation is normally greater than the Haversine distance due to speed limits, congestion and driving rules ([5], P: 187). To solve this problem, travel distance and travel time can be obtained through repeated calls to the Google Maps Web page using Python 2.7. Then, a regression analysis can determine the relationship between real world distance and the Haversine distance (refer to the case study section for more information).

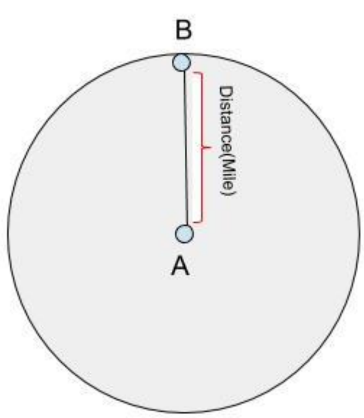

Figure 3: Desired area for ride matching

When it comes to the urban facilities, budget is always a main constraint for future development. So, any urban development project needs to be aligned with the city’s budget by proposing minimum new development and utilizing existing facilities at its highest possible rate. However, such options are not the most favorable ones in terms of planning goals. In a challenge between budget and efficiency, finding the optimum solution is the hardest part of any urban planning decision making process.

Likewise, allocation of ridesharing facilities is a game between the optimum number of stations that impose the fewest costs to the city from one side, and on the other hand, does not require long wait times and covers as many areas as possible. This makes the allocation of ridesharing facilities a Multi-Criteria Decision Making Process which is required to make a choice between different scenarios that are proposing different combinations of number of stations, desired wait time, and the total number of nodes that can be served by the facilities.

Multi-Criteria Decision Analysis (MCDA)

Multi-Criteria Decision Analysis, (MCDA), a powerful analysis tool that incorporate qualitative and quantitative analysis to solve problems that are characterized as a choice among different factors and alternatives. Dividing the decision into smaller parts, MCDA makes the decision-making process simpler and more understandable. Through a logical and consistent process, MCDA helps researchers in analyzing each part individually and then integrating them in order to compare alternatives and make the final decision. The following paragraphs describe the MCDA steps.

a) Defining the goal of analysis and the decision variables

The Goal of the research mostly describes the primary focus of the research. So when the goal is defined, we can also think about the contributing factors and their effects on the main goal. These factors are also the basis for comparing the alternatives.

b) Defining criteria rank with respect to the goal of the analysis

Defining how one criterion is preferred over the other in a one by one comparison, criteria will be ranked with respect to the goal of the analysis. The following table shows some suggested values for criteria ranking.

Table 1: Suggested values for pairwise comparison in MCDA

Option	**Numerical value(s)**
Equal	1
Marginally strong preference	3
Strong preference	5
Very strong preference	7
Extremely strong preference	9
Intermediate values to reflect fuzzy inputs	2, 4, 6, 8
Reflecting dominance of second alternative compared with the first	Reciprocals

Source: ([12], P:17)

c) Computing the vector of criteria weights

criteria weights will help us to find the optimum solution for the problem. So, after ranking the criteria we need to calculate the geometric mean of the values (weight) for each criterion. The geometric mean of a data set $\{a_1, a_2, \ldots, a_n\}$ is given by:

$$G = \sqrt[n]{a_1 a_2 \cdots a_n}.$$

Then it is time to normalize the weights. To normalize the weights, the geometric mean of each criterion should be divided by the sum of all of the weights.

Table 2: Pairwise comparison of decision-making criteria

criteria	H	W	N	Geometric mean (weight) of the criterion	Normalized weights
H	1	R_{H1}	R_{H2}	G_H	$W_{H=}$ G_H/sum
W	1/R_{H1}	1	R_{w1}	G_W	$W_{w=}$ G_W/sum
N	1/R_{H2}	1/R_{w1}	1	G_N	$W_{N=}$ G_N/sum
Sum				Sum= G_H +G_w +G_N	1

d) Designing Alternatives

Alternatives are different scenarios that are defined by various combinations of decision-making criteria. Having different alternatives helps the researcher to monitor the extent that a criterion can affect the final result.

Table 3: Alternatives pairwise comparison

Alternative	H	W	N
A	V_{1a}	V_{2a}	V_{3a}
B	V_{1b}	V_{2b}	V_{3b}
C	V_{1c}	V_{2c}	V_{3c}

e) Scoring the Alternatives

Lastly, for each of the alternatives, the value of desired criterion will be multiplied by the normalized weight of that criterion. The final score of each alternative comes from sum of the all of the scores of the criteria.

Table 4: Alternatives final scores

Alternative	H	W	N	Final Score
A	$V_{1a}* W_H$	$V_{2a}* W_w$	$V_{3a}* W_N$	$S_1=V_{1a}* W_H+ V_{2a}* W_w+ V_{3a}* W_N$
B	$V_{1b}* W_H$	$V_{2b}* W_w$	$V_{3b}* W_N$	$S_2=V_{1b}* W_H+ V_{2b}* W_w+ V_{3b}* W_N$
C	$V_{1c}* W_H$	$V_{2c}* W_w$	$V_{3c}* W_N$	$S_3=V_{1c}* W_H+ V_{2c}* W_w+ V_{3c}* W_N$

Part Two: Geographic Allocation of Ridesharing Facilities

Sixth: Identifying the most favorable shared-trips' origins and destinations

So, after following the MCDA steps and finding the optimum number of the stations and wait time, we can identify the shareable trips, based on the following algorithm. The graph explains that the only shareable trips are those which start and end within specific time and distance zone.

When shareable trips are identified, results can be visualized using ArcGIS. Point density can describe the potential hottest and coldest areas in terms of demand for ridesharing.

Seventh: Identifying the optimum locations for ridesharing facilities

As the final step of the model, results of previous steps should be combined to create a reliable basis for further planning decisions. So, a map that includes the location of public parking, geographic location of potential hot spot for ridesharing demands and proposed location for ridesharing facilities is the desired output of this step. This final map should be integrated with the knowledge of urban planning about the future development plan of the city, scio-economic status of the neighborhoods that the ridesharing facilities are suggested to be located within and also high-level political and social decisions, to build the pillars of the final suggestions for allocation of ridesharing facilities in a city.

Ann Arbor Case Study

Ann Arbor is one of the mid-size cities in the state of Michigan. The city's population was estimated at 117,070 as of July 2015 by the U.S. Census Bureau. [19] According to the National Household Travel Survey, Ann Arbor residents had driven their cars for 740000 trips per day. On average, each vehicle was driven for 8.3 miles per trip at an average length 16.8 minute and speed of 30 mph. The average number of vehicles occupant in each trip was 1.6 per vehicle-trip.[1]

First: Selecting a random 24 hours

For sure, no urban facility allocation decision can be made just based on the analysis for one day. However, since the main purpose of this study is to establish a model and build a framework for such problems, 24 hours is a good period of time to study the shareability pattern. Considering the weather

[1] U.S Department of Transportation. 2009 National Household Travel Survey. Data for Detroit, Ann Arbor and Flint area.

condition, school season and level of seasonal activities, a weekday on September 2012 is chosen for this study.

Second: Selecting study area

Like what was suggested earlier, a few miles distance from official city borders may help planners to efficiently consider commuter trips into their calculations. This distance may differ from a city to another. In the case of this thesis's case study, a 2-mile distance is chosen based on the spatial distribution pattern of trips.

Third: Identifying the most favorable trips' origins

Using ArcGIS 10.4.1 the following map shows which areas in City of Ann Arbor produce more trips in relative to other areas.

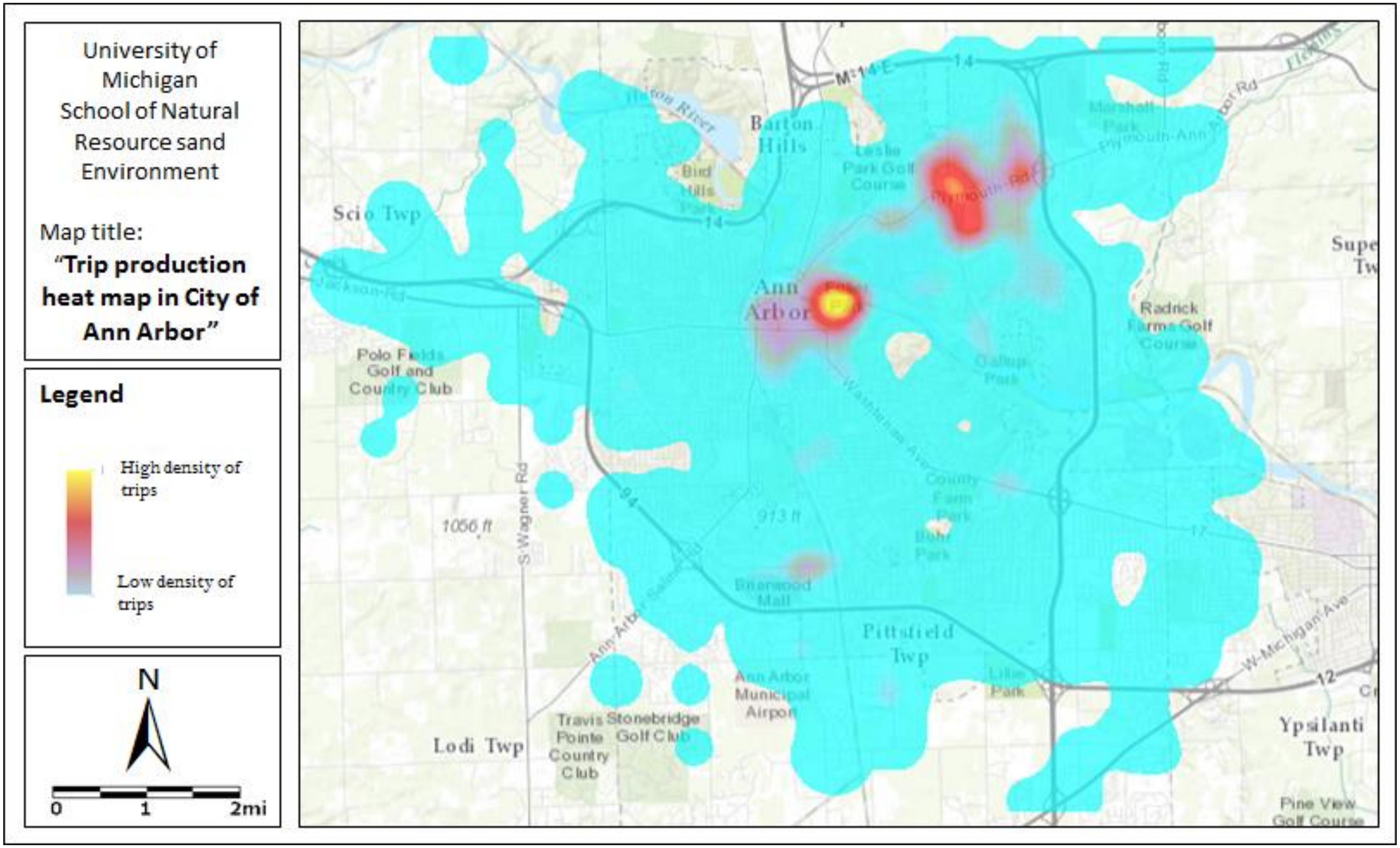

Figure 4: Trip production heat map in Ann Arbor, M

Fourth: Identifying the most favorable trips' destinations

After finding favorable areas for trip generation, this time it is needed to find areas that absorb a greater number of trips relatively. Figure 5 shows hot trip absorption areas in the City of Ann Arbor.

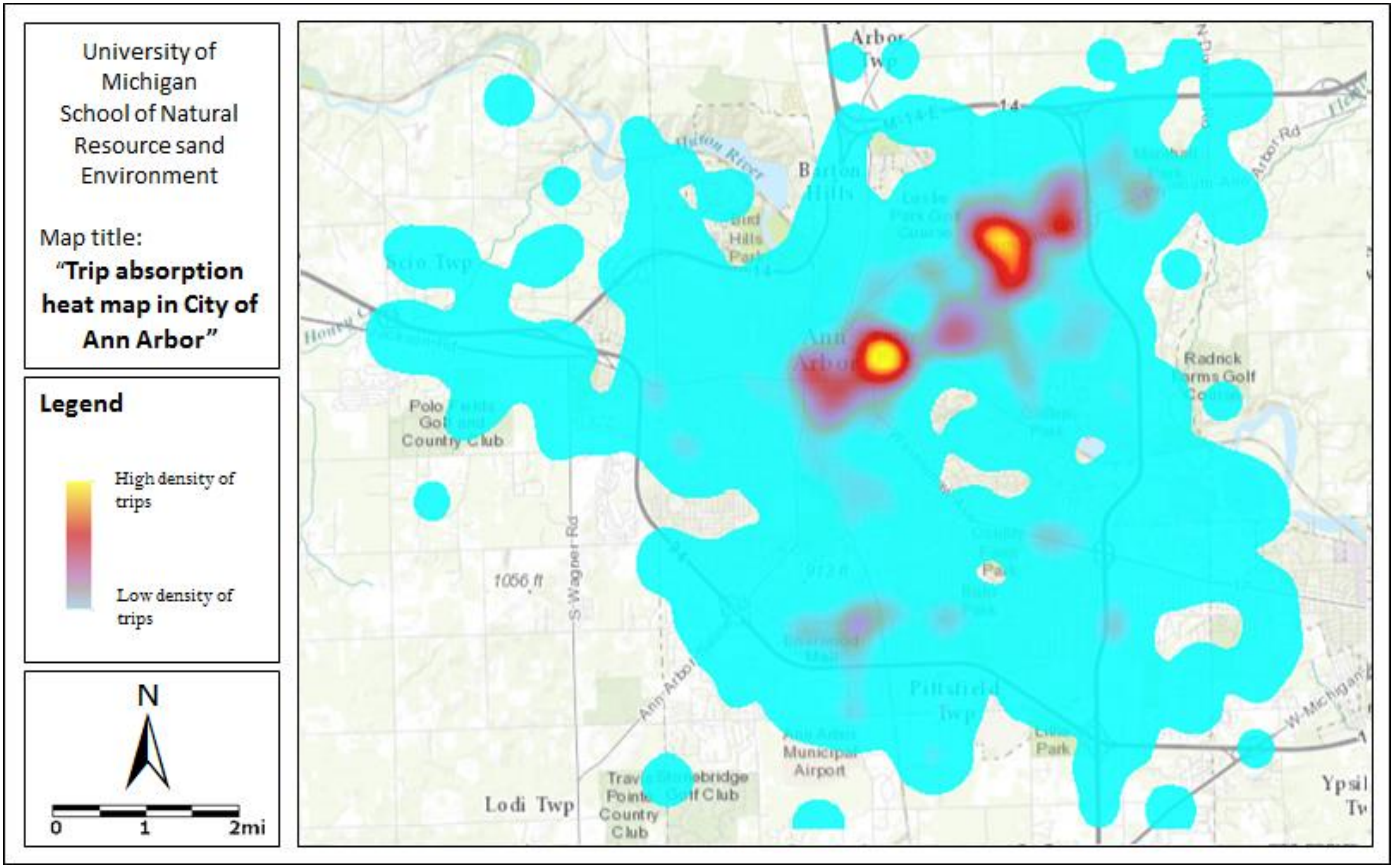

Figure 5: Trip absorption heat map in Ann Arbor, MI

Fifth: Defining and identifying shareable trips

Finally, to find possible shareable trips in the city of Ann Arbor, we need to define speed, wait time and distance. So, based on the average speed in the area, 30 miles/hour was chosen as the average speed of the vehicles. In order to figure out the relationship between driving distance and the Haversine distance, a regression analysis is performed. As is shown in Figure 6, with a high level of statistical reliability, driving distance between two nodes in Ann Arbor follows the following formula:

$$D\ (Oi - Oj) = 1.5255 * HD\ (Oi, Oj)+0.1338$$

where HD (Oi, Oj) is the Haversine distance between point Oi and Oj.

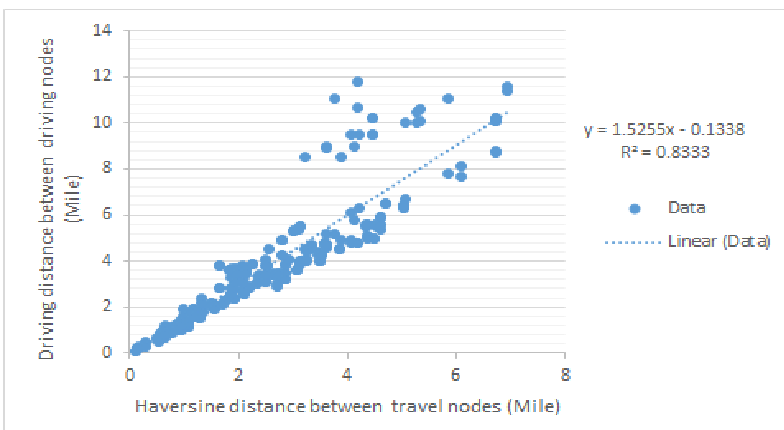

Figure 6: Relationship between Haversine Distance and driving distance (R2 = 0.8333 for the fitted line)

Multi-Criteria Decision Analysis (MCDA) for the Ann Arbor Case Study

In this research, the following steps are taken to find the optimum option that has the best combination of number of stations and wait time.

a) Defining the analysis goal and the decision variables

As was mentioned earlier, in this research the goal is finding the best option that has the optimum number of stations and length of wait time. Thus, the system can be sketched according to the following graph:

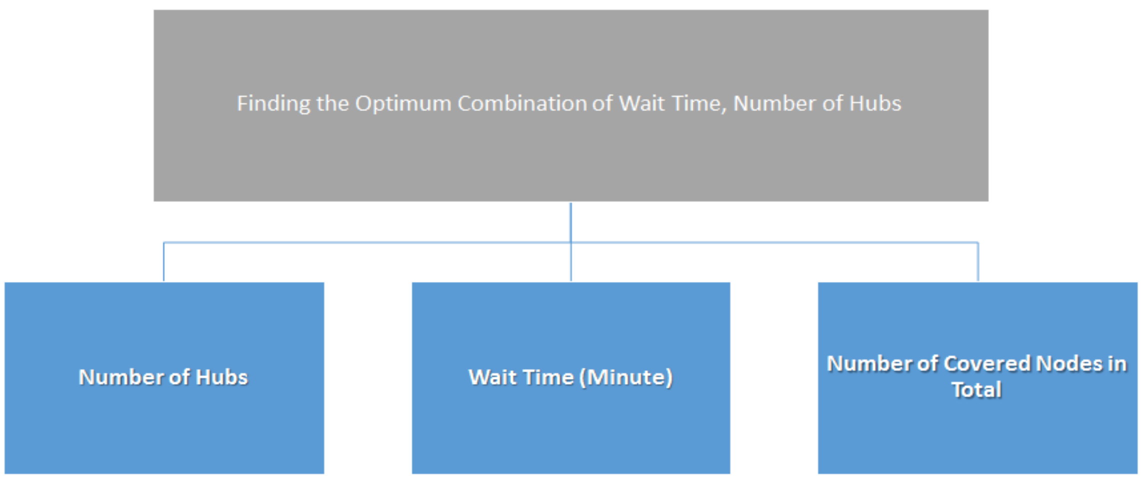

Figure 7: Hierarchy of MCDA criteria with regards to the research goal

b) Defining criteria rank with respect to the goal of the analysis

Criteria ranking is the most complex part of the MCDA as it needs the researcher to make a decision about preferences. The decision should also consider budget limitations and passengers' tolerance time at the same time as the size of the population will be served by these services. Table 5 shows the suggested values for criteria ranking in this research.

Table 5: Criteria rank with respect to the goal

	Station	Wait time	N-covered
Station	1	3	5
Wait time	0.333	1	3
N-covered	0.2	0.33	1

c) Computing the vector of criteria weights

As explained before, at this stage, criteria weights should be calculated and then normalized. The following table shows the normalized weights.

Table 6: Criteria weights with respect to the goal

Criteria	Geometric mean (weight) of the criterion	Normalized weights
Station	2.466212074	0.6372636685
Wait time	0.9996665555	0.2583115958
N-covered	0.4041240021	0.1044247357
Sum	**3.870002632**	**1**

d) Designing Alternatives

Wait time:

Wait time is dependent on many different factors. So, any decision about wait time is only reliable when it considers these factors. In conducting this research, in order to have a better estimate of desired wait time, three different values (5, 7.5 and 10 minutes) for wait time are considered. These values are chosen based on the values used in the previous research. ([1], [2], [6]-[9], [15]-[17], [23], [24])

Number of stations:

The number of stations is another definitive factor that can greatly affect any allocation decision. The first estimate of the number of hubs comes from the result of the third and fourth step of the shareability assessment model. In case of Ann Arbor, this value was around 5 stations. Other scenarios that suggest 4,6 and 7 stations consider the limitation of the city budget and efficiency of the ridesharing system.

Number of Covered Nodes:

Integrating the number of stations, wait time period, distance and speed, this factor shows how efficient the ridesharing system works in order to respond to ridesharing requests. The number of covered nodes is also a representation of the geographic distribution of the stations. In the other words, if the stations are homogeneously distributed within the city, there is a great chance of missing some of the nodes that are not within the desired ridesharing distance of the station. Conversely, stations that are in the areas with a higher density of nodes can cover more nodes with ridesharing possibility. So, it is obvious that the number of covered nodes is correlated with the geographic allocation of hubs. Therefore, a reliable algorithm for clustering nodes (with ridesharing potential) is necessary. In this research two algorithms are proposed:

i) K-means Clustering Algorithm:

K-means clustering algorithms take a matrix of M points in N dimensions and spread the nodes into K clusters in a way that the within-cluster sum of the squares is minimized. In this way, it is assured that cluster centers are in their optimum location as no movement of a point within clusters will reduce the within-cluster sum of the squares. ([10], P: 100) In this research, a matrix of all of the trip nodes in one day (9/10/2012) is used as the algorithm input. There are also four different values for the number of stations (4, 5, 6 and 7) tested and used as the number of clusters (with various wait time values) to create the first 12 alternatives. (Table 7)

ii) Hub finder Algorithm:

This is the algorithm developed by the author. The basis for the hub finder algorithm is the number of nodes that any given node has the potential to share a ride with. Logically, the best location for a station is a place that it is surrounded by the highest number of potential ridesharing service users. So, in this algorithm, after identifying the shareable trips, the number of nodes that can share a ride with a specific node will be calculated. This process will be repeated for every single travel node in the database. Then the node that has the highest number of connected nodes will be selected as a hub. When the first station is found, this node and associated nodes (nodes that can share a ride with it) will be removed from the whole list of nodes. Then the same process will be repeated for the remaining nodes. This process continues until the desired number of stations with associated nodes are all found. The output of the model is geographic location of the stations as well as the number of nodes that will not be covered with this system of clustering. The following script explains the model:

Input= All of the trip nodes

H= proposed number of hubs

D= Desired Distance between nodes for forming a shared trip

W= Desired wait time between nodes for forming a shared trip

max_node = The node that has highest potential (highest value of count) for ridesharing among the dataset

connected = A set of nodes that contains all of the nodes that can do ridesharing with one node.

new_connected= A set of nodes that contains the max-node and all of the nodes that it can do ridesharing with.

count = number of potential nodes that one node can share a ride with

max_count= The highest value of count

Remainder= Number of nodes that can’t be covered by the suggested system ridesharing (number of hubs and wait time)

```
1) WHILE hub < H:
2) FOR node-a and node-b in Input:
3) IF distance(node_a, node_b) <= D THEN:
4) IF time (node_a, node_b)<= W THEN:
5) ADD (node_b) to connected
6) count= LENGTH (connected)
7) ENDIF
```

```
8) IF count > max_count THEN:
9) max_count = count
10)       max_node = node_a
11)       ADD max_node, connected to new_connected
12)       DELETE new_connected from Input
13)       Remainder=LENGTH(Input)
```

Pairing different wait time values with different number of hubs and methods of clustering, 24 alternatives are generated.

Table 7: Allocation of ridesharing facilities alternatives

Alternative	Wait time (min)	N-Hub	N-Covered
1	**5**	**4**	**911**
2	**7':30"**	**4**	**1183**
3	**10**	**4**	**1257**
4	**5**	**5**	**1070**
5	**7':30"**	**5**	**1234**
6	**10**	**5**	**1260**
7	**5**	**6**	**1093**
8	**7':30"5**	**6**	**1236**
9	**10**	**6**	**1260**
10	**5**	**7**	**1113**
11	**7.5**	**7**	**1244**
12	**10**	**7**	**1260**
13	**5**	**4**	**957**
14	**7':30"**	**4**	**1174**
15	**10**	**4**	**1255**
16	**5**	**5**	**1030**
17	**7':30"**	**5**	**1233**
18	**10**	**5**	**1261**
19	**5**	**6**	**1103**
20	**7':30"**	**6**	**1251**
21	**10**	**6**	**1264**
22	**5**	**7**	**1152**
23	**7.5**	**7**	**1260**
24	**10**	**7**	**1267**

e) Scoring the Alternatives

As the final step of the MCDA, each alternative should be scored. Table 8 shows alternatives final scores.

Table 8: Final score of alternatives

Alternative	N-Hub	Wait time (min)	N-Covered	Alternative Score
1	**4**	**5**	**911**	**82.29**
2	**4**	**7':30"**	**1183**	**733.15**
3	**4**	**10**	**1257**	**376.40**
4	**5**	**5**	**1070**	**96.21**
5	**5**	**7':30"**	**1234**	**764.73**
6	**5**	**10**	**1260**	**377.91**
7	**6**	**5**	**1093**	**98.47**
8	**6**	**7':30"5**	**1236**	**766.05**
9	**6**	**10**	**1260**	**378.52**
10	**7**	**5**	**1113**	**100.48**
11	**7**	**7.5**	**1244**	**2.83**
12	**7**	**10**	**1260**	**0.86**
13	**4**	**5**	**957**	**86.23**
14	**4**	**7':30"**	**1174**	**727.59**
15	**4**	**10**	**1255**	**375.80**
16	**5**	**5**	**1030**	**92.78**
17	**5**	**7':30"**	**1233**	**764.1123**
18	**5**	**10**	**1261**	**378.20**
19	**6**	**5**	**1103**	**99.33**
20	**6**	**7':30"**	**1251**	**775.31**
21	**6**	**10**	**1264**	**379.71**
22	**7**	**5**	**1152**	**103.82**
23	**7**	**7.5**	**1260**	**2.83**
24	**7**	**10**	**1267**	**0.86**

MCDA Results

As the results reveal, among all of the scenarios, 7.5 minutes wait time gained better scores than others. Considering the number of hubs, seven stations are absolute losers in all of the cases. Although 6 hubs and 7.5 minutes wait time in both clustering methods (alternative 8 and 20) have the highest scores, but there is not a considerable difference between 5 hubs with the same waiting time (alternative 5 and 17). So, alternative 5 and 17 are our best choice for the allocation of ridesharing facilities. The final decision between scenarios can be made after the geographic allocation of each scenario at the city level.

Sixth: Identifying the most favorable shared-trips origins and destinations

The following map represents a heat map of the areas with high to low potential for forming a shared trip. As it could be predicted from the primary maps generated in steps three and four, University Hospital and North Campus have the highest potential for ridesharing.

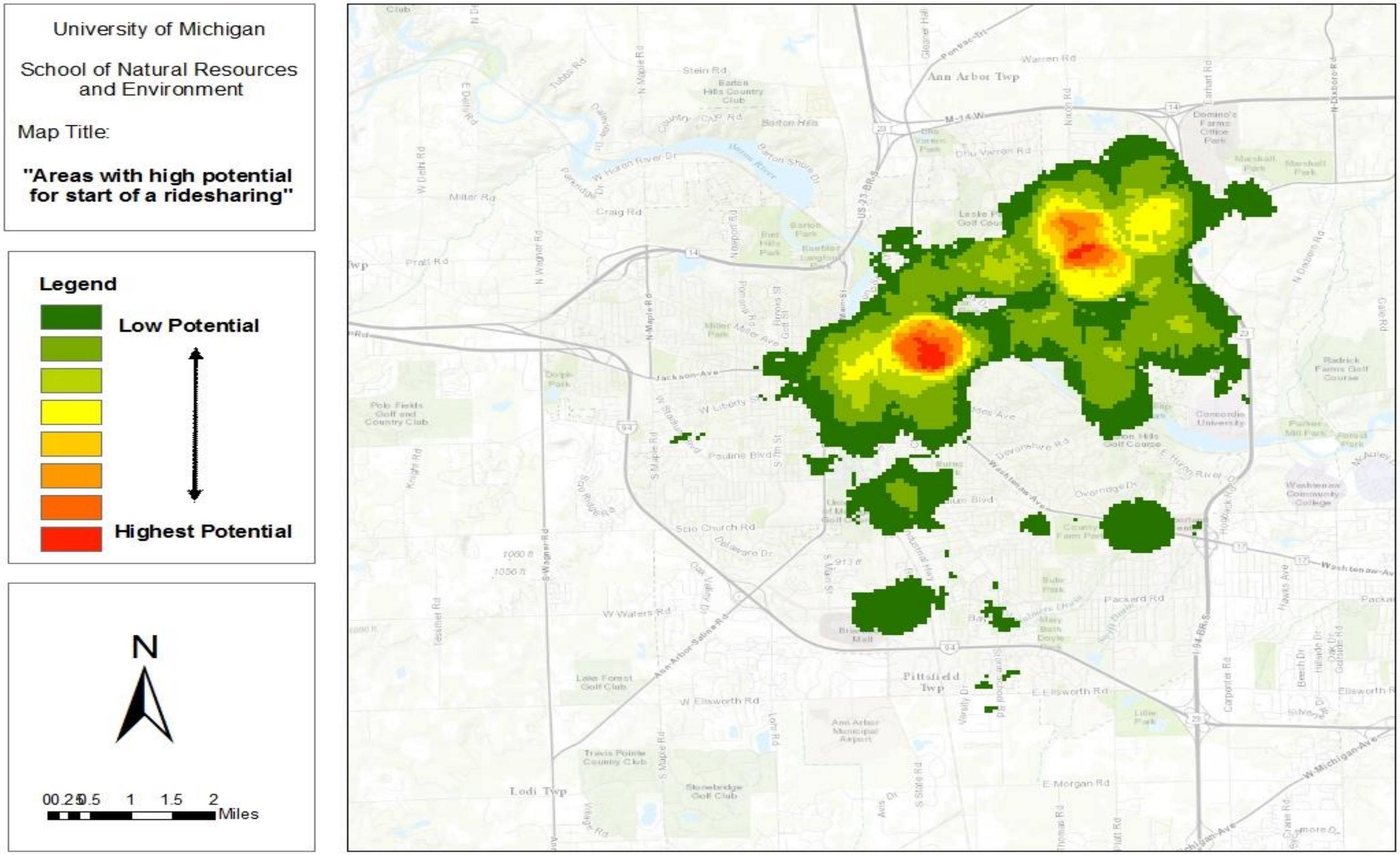

Figure 8: Areas with high potential for ridesharing

Seventh: Identifying optimum locations for ridesharing facilities in city of Ann Arbor using ArcGIS

For this step, first we need to analyze the pattern of geographic allocation of stations coming from the previous step. As mentioned before, scenarios that proposing 5 hubs with 7 minutes and 30 seconds, are our optimum solutions for the allocation of ridesharing facilities. So, using ArcGIS 10.4.1 software, the following map shows the results.

As can be inferred from the map, the k-means algorithm represents many reasonable results considering the extent of serving areas and geographic distribution of stations within the city borders. Hence, the hubs found in the k-means algorithm will be used as the location of potential ridesharing facilities.

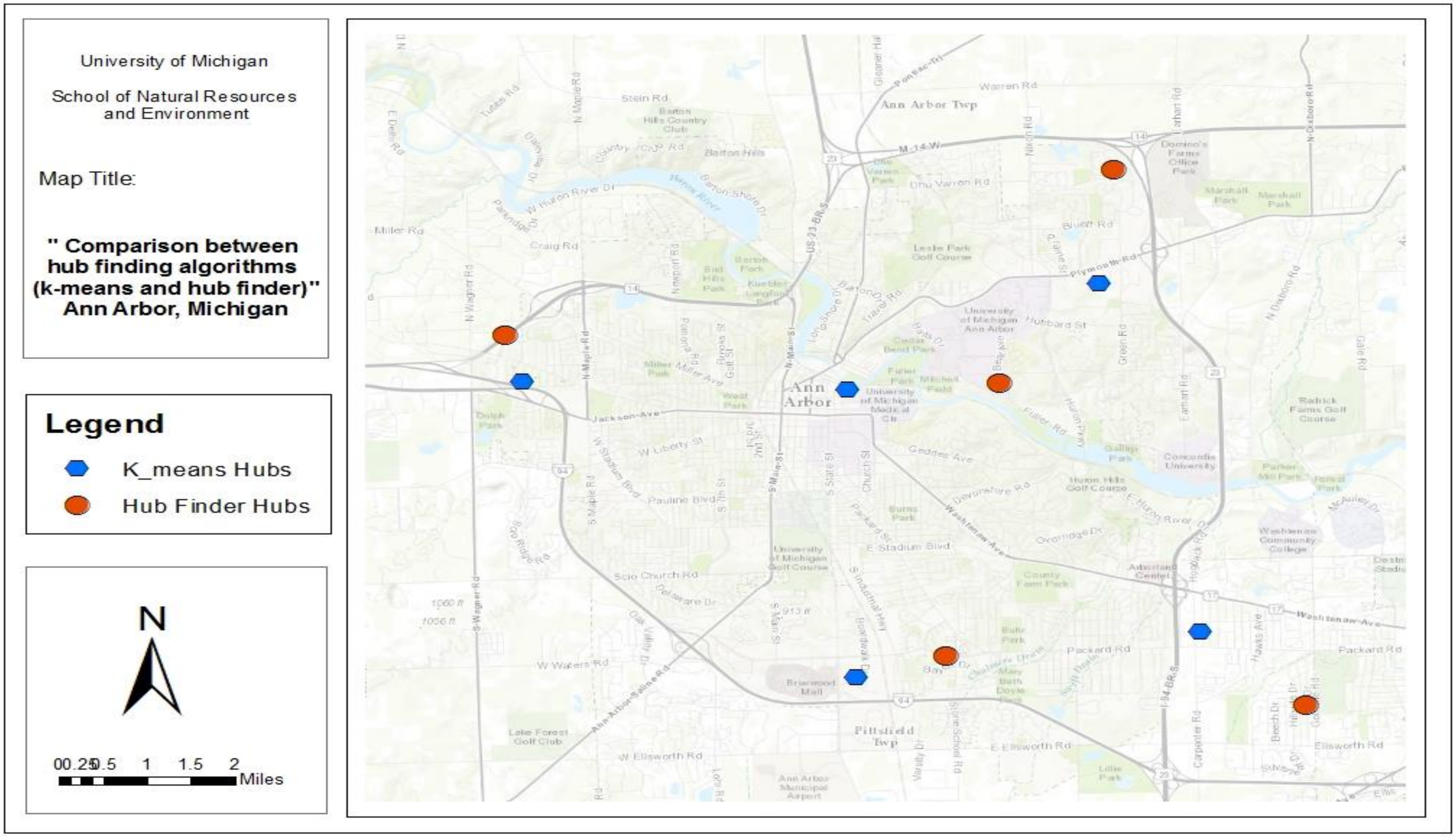

Figure 9: Comparison between hub finding algorithms (k-means and hub finder) for the Ann Arbor Case study

Comparing the suggested facilities' location with current public parking locations and hot trip demand areas, figure 10 shows the optimum location of future ridesharing facilities. Those areas that already have public parking, can take advantage of them to move toward more environmental savings. For the node that does not have any neighboring public parking (upper right side of the map) based on our field knowledge, we know that there are several university-owned parking spots (North Campus Research Complex) that are underutilized most of the time. So, a partnership between U of M and the city of Ann Arbor can solve the problem in a more sustainable manner.

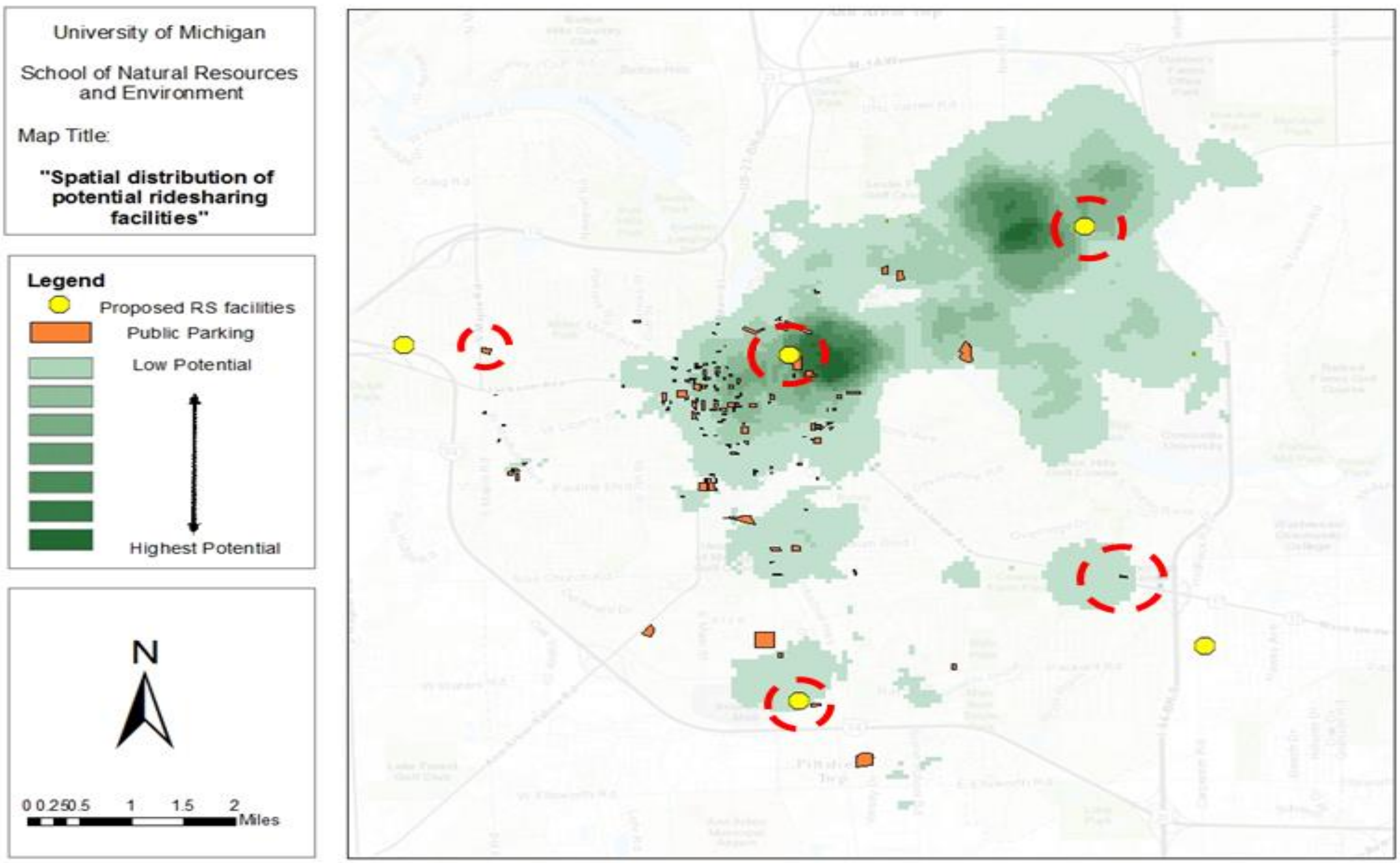

Figure 10: Spatial distribution of proposed ridesharing facilities in Ann Arbor, MI

Discussion

Through this thesis, we figured out the travel pattern in the city of Ann Arbor. Then based on a couple of logical steps and assumptions, we predicted the demand for ridesharing in the city and identified hotspots for trip production and absorption. Plain travel patterns and predicted ridesharing demand map both show that the downtown area and the U of M North Campus are two of the hottest areas for travel demand. Results revealed that the predicted ridesharing system requires five stations in specific geographic locations to assure the optimum duration of passengers' wait time of seven and half minutes. This system could have many environmental and social benefits for the city of Ann Arbor that will be discussed later in this section.

As one of the old mobility services, ridesharing has evolved through its history to meet customers' demands with a higher quality of service. With the rise of sustainability concerns since 1980's, today citizens are looking for services that not only provide them with high-quality services but also care about their sustainability concerns. In the case of Ann Arbor, this is not only a demand from users. In fact, as the home of the University of Michigan (U of M), one of the leading universities in sustainability practices. Ann Arbor faces considerable demand from the city council to utilize sustainable transportation services as much as possible.

Translating findings of this thesis into urban and regional planning strategies and transportation systems provision will provide much utility for promoting sustainable transportation services. In case of the Ann Arbor, sustainability benefits from the proposed system of ridesharing can be explained through following practices:

- **Environmental**

Environmental benefits are generally associated with ridesharing services. However, there are also greater environmental savings that this research is trying to address. Primary, optimized allocation of ridesharing facilities reduces energy usage, VMT and greenhouse gas emissions. This occurs because vehicles don't have to just move around until two passengers call for a service or spend time finding a parking space during idle time. Ridesharing vehicles can easily navigate toward one of the proposed facilities and wait there until somebody calls them. This can considerably decrease the empty vehicles' routing time and mileage as well as associated fuel usage and emissions.

Based on the findings of this research, if we assume that all of the shareable trips would be shared between two people then 49% of daily trips are going to be saved. From our data, it is also known that each average trip length is about 3.64 miles in the study area. Therefore, we could expect 2246 mile VMT savings per day if ridesharing took place.

Additionally, to calculate the pollutant reduction from vehicles exhaust, the following well-to-tank emission factors for Gasoline Passenger Cars (models 2009-present) are used: 3.6 g/mile for CO, 0.3 g/mile for NO_x, 0.28 g/mile for VOCs, 0.038 g/mile for $PM_{2.5}$ and 0.08 g/mile for PM_{10}. Table 9 shows the results. ([11], P: 1799- 1803)

Table 9: Expected pollutant reduction from ridesharing in city of Ann Arbor

Pollutant	g/mile	Total Emissions Savings
VOC	0.28	628.88
NO_X	0.3	673.8
PM_{10}	0.08	179.68
$PM_{2.5}$	0.038	85.348
CO	3.6	8085.6

Using the GHG Inventory Guidance GHG Inventory Guidance and assuming an emission factor of 0.0173 gr per mile for CH_4, 0.0036 gr per mile for N_2O and 411 gr per mile for CO_2 for Gasoline Passenger Cars (models 2009-present), our results show that the proposed system of ridesharing can improve the environmental sustainability of Ann Arbor by cutting at average, 39 gr of CH_4, 8 gr of N_2O, and 923106 gr of CO_2 from the current daily level of emissions. (Table 10) ([22], P: 2 & [21], P: 18)

Table 10: Greenhouse gas emissions reduction from ridesharing in city of Ann Arbor

GHG	g/mile	Total Emissions Savings
CH_4	0.0173	38.86
N_2O	0.0036	8.09
CO_2	411	923106

Also from the demand perspective, when the stations are optimally allocated, the quality of ridesharing services is guaranteed in terms of the standard wait time and distance from potential customers. So, because of the reliability of the service, more people may use these services as their main means of transportation. The shift in demand is expected to occur especially from students who wants to save more on vehicle ownership costs while they are studying away from their hometown. Therefore, there would be greater environmental savings.

Last but not least, by using existing parking facilities, ridesharing in Ann Arbor also contributes to lower environmental damages from building new parking lots and new road lanes in the future. Generally, each component of mode shift, from private vehicle to the optimized ridesharing services, impacts the total environmental damage reduction differently.

- **Sustainable Urban Development**

With the proposed system of ridesharing facilities, further progress toward sustainable urban development is predicted in the city of Ann Arbor. By reducing the number of vehicles on roads, less road congestion will be easier to be managed by the city traffic management authorities.

One of the main advantages of the proposed ridesharing facilities system is that it is based on utilizing the existing infrastructure. As explained in the final step of the model, in order to minimize the cost of developing facilities and preventing new costs, proposed stations can be minimally relocated to the nearest existing public parking facilities. In addition to the cost savings, this can contribute to environmental sustainability by cutting the need for spending energy on building new parking facilities and new road lanes.

Also for the sake of sustainable land use practices, U of M and the Ann Arbor city council can establish an agreement that allows development of ridesharing facilities in those of university-owned parking spaces, which currently are not being used at their highest capacity.

- **Pave the way for automated connected vehicles**

Although using private vehicles for everyday commute may be different from using ridesharing services, the framework and methods developed in this research can be applied to private vehicles when data for trip origins and destinations become available at the large scale. This is also true about prediction of future demand for shared autonomous vehicles (SAV) in urban areas. Like what was discussed before, with the help of optimally located ridesharing facilities, future demand for SAVs could be met at considerably low environmental costs. This also has high importance for the city of Ann Arbor, as the city is getting ready to host the incoming wave of SAVs in the following years. With the U of M's ambitious plans for implementing its own lane of connected autonomous vehicles, allocation of ridesharing facilities can build a strong partnership between the university and the city council on sharing available facilities, like extra capacity of parking lots.

Conclusion

A powerful analytics model has been developed for evaluating potential ridesharing opportunities, with a particular emphasis on a system of stations that offer services related to ridesharing. Initially, the model has been applied to Ann Arbor in Michigan. A good deal of effort went into designing such a system for this area, including understanding the characteristics of the transportation system and the travel pattern in this area. Additionally, with the help of strong analysis tools like MCDA and Regression analysis, this thesis developed an effective model to predict ridesharing demand and to allocate necessary facilities. Also the findings of this thesis express that with a 7.5 minutes wait time and 6 ridesharing stations, 97 percent of nodes will be covered with reliable ridesharing services. Also with the proposed stations system, there is a good chance of using nearby public parking to move toward greater environmental savings. The result of this thesis shows that at the highest level of adoption, the system can save 2246 mile of VMT every day which can lead to cutting 39 gr of CH_4, 8 gr of N_2O, and 923106 gr of CO_2 from current daily level of emissions. Although this model was initially developed for the city of Ann Arbor, it can be easily applied to numerous other case studies with demand for shared vehicle systems.

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